Training Course in the integration of the impact of environment on stocks productivity in Management Strategy Evaluation models

Fitting relationship to data: Recruitment

Isabella Bitetto

Fondazione COISPA ETS

SEAwise has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 101000318

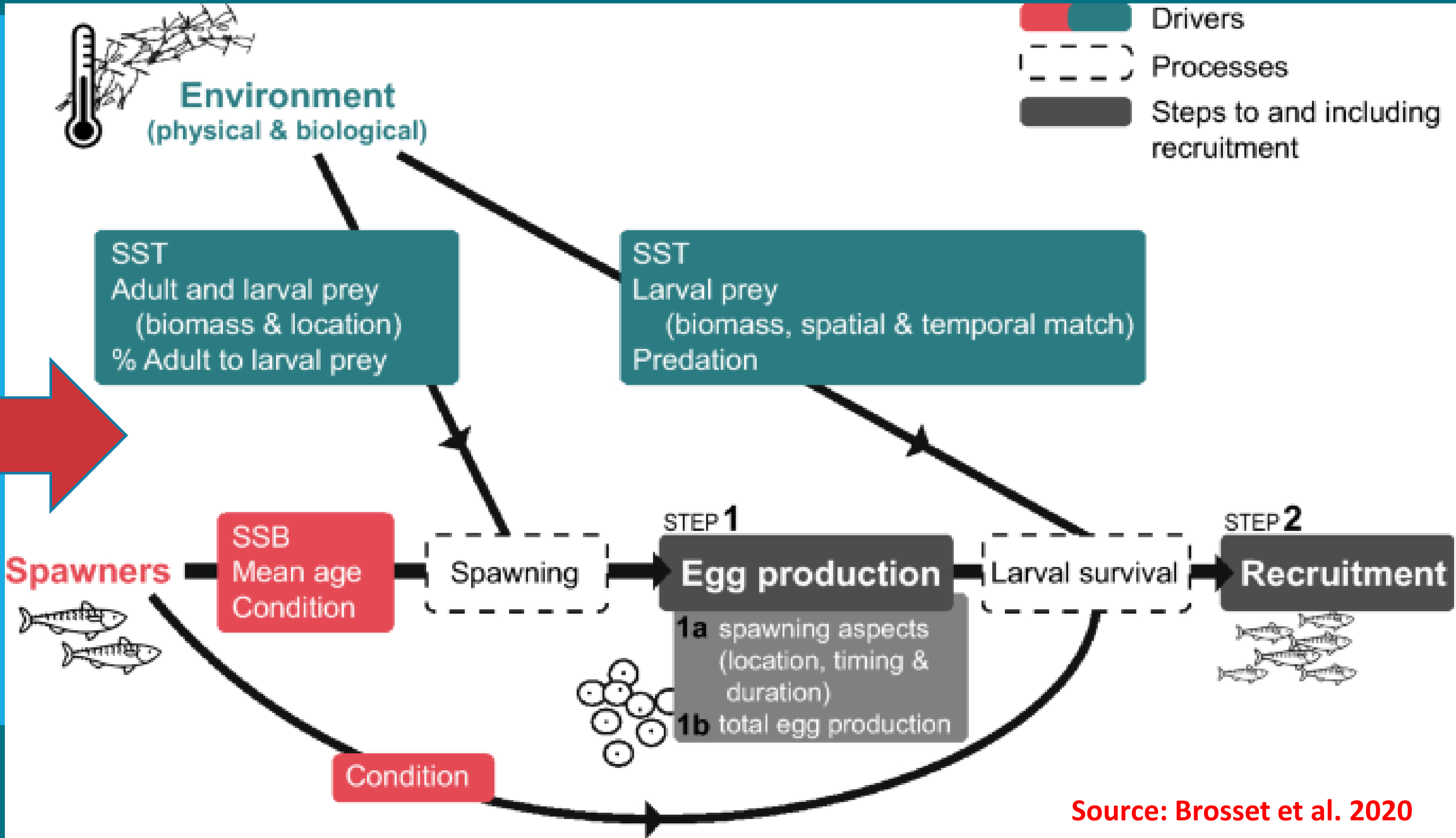
Background

- Environmental factors are major drivers of the variability in the marine populations and ecosystems.
- Environment influences the recruitment of marine fishes through physiological processes or by inducing shifts in the zoo-plankton community, representing the main food items for new born fishes.
- The use of stock recruitment relationships is useful to support the **estimation of reference points** (e.g., STECF, 2022) and accounting for climate changes allows to take into consideration the evolution of the stock dynamics accounting for multiple factors.

Recruitment is one of the key processes regulating fish population productivity

Result of several factors:

- total egg production (TEP);
- eggs survival;
- stock demographics (e.g. **SSB, age structure, and maternal body condition)**.

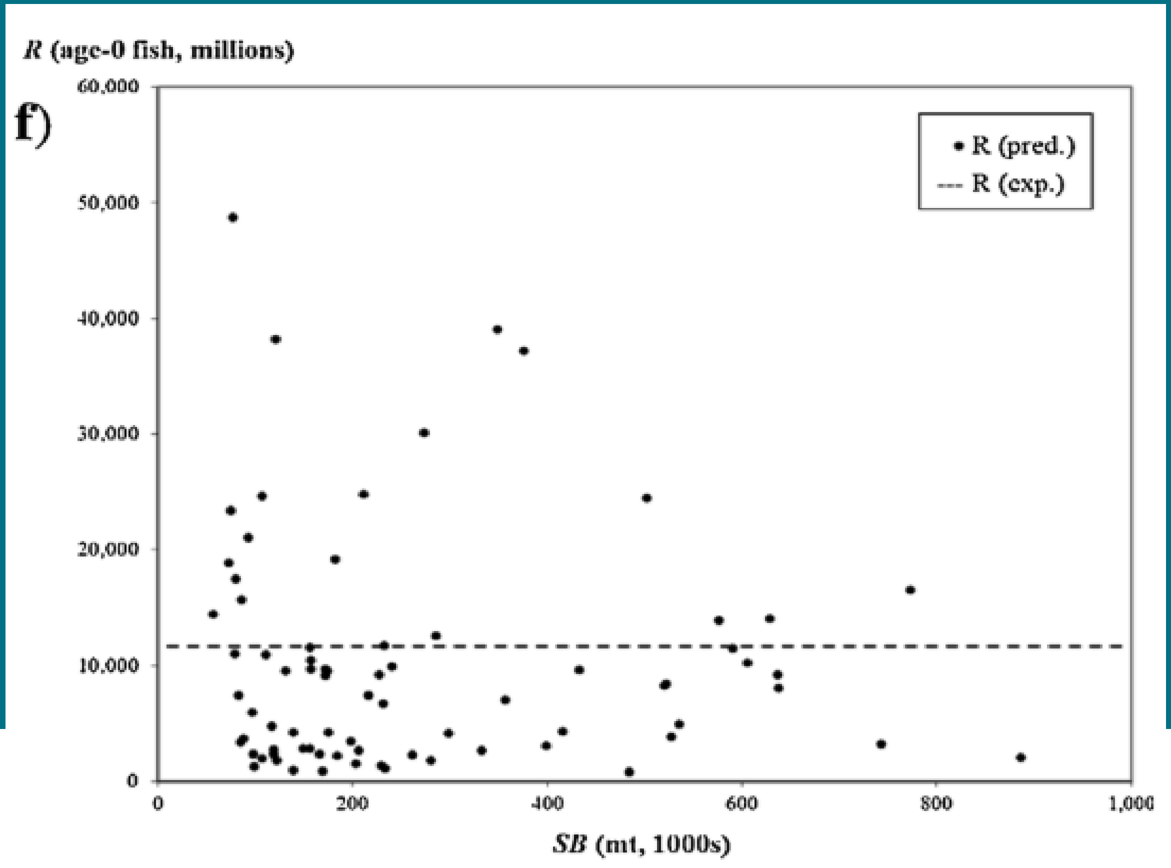


Source: Brosset et al. 2020

Linking recruitment variations to environmental variables

In the recent literature, some stock-recruitment models were extended to include the influence of the environmental factors on the recruitment (Olsen et *al.*, 2011; Akimova et al., 2016; Romagnoni et *al.*, 2019).

1. ***process error:*** stock-recruitment relationship assumed as stationary (Crone et al., 2019) and annual variation considered as a function of environmental covariates



Source: Crone et al., 2019

$$RecDev(t) \sim N\left(0, {\sigma^2}_{tot}\right)$$

$${\sigma^2}_{tot} = {\sigma^2}_{env} + {\sigma^2}_{rand}$$

${\sigma^2}_{env}$:recruitment variability attributed to **environmental index**

${\sigma^2}_{rand}$: recruitment variability attributed to **unexplained random variation**

Literature

Linking recruitment variations to environmental variables

In the recent literature, some stock-recruitment models were extended to include the influence of the environmental factors on the recruitment (Olsen et *al.*, 2011; Akimova et al., 2016; Romagnoni et *al.*, 2019).

2. ***model error:*** **parameters** of the stock-recruitment relationship **varying over time**, depending on environment (Berger, 2019)

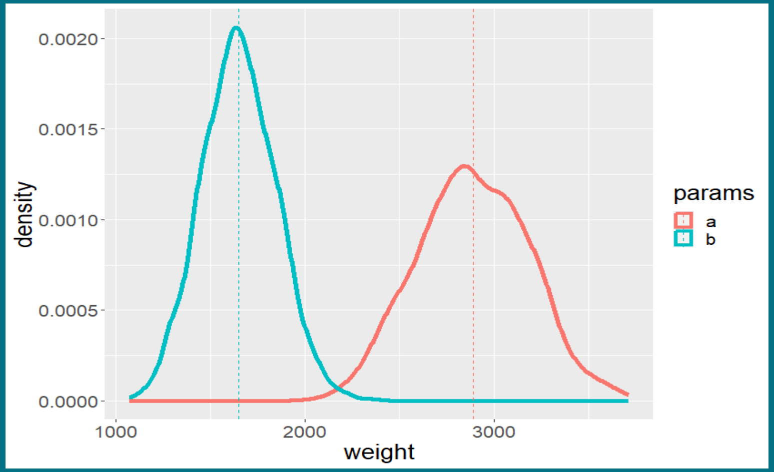
$$Rec = a * \frac{SSB}{1 + b * SSB}$$

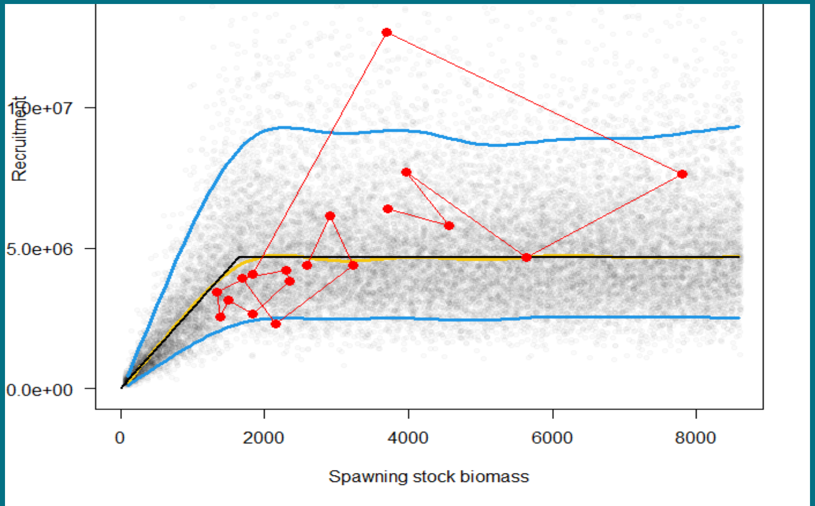
$$a \sim N\left(0, \sigma^2_{a,env}\right)$$

$$b \sim N\left(0, \sigma^2_{b,env}\right)$$

$\sigma^2_{a,env}$:variability attributed to **parameter *a* due to environmental** index

$\sigma^2_{b,env}$:variability attributed to **parameter *b* due to environmental** index





more data demanding!!!

Literature

Several studies showed that the first approach performs in a satisfactory way, although less data demanding (Sharma et al., 2019; Levi et al., 2003).

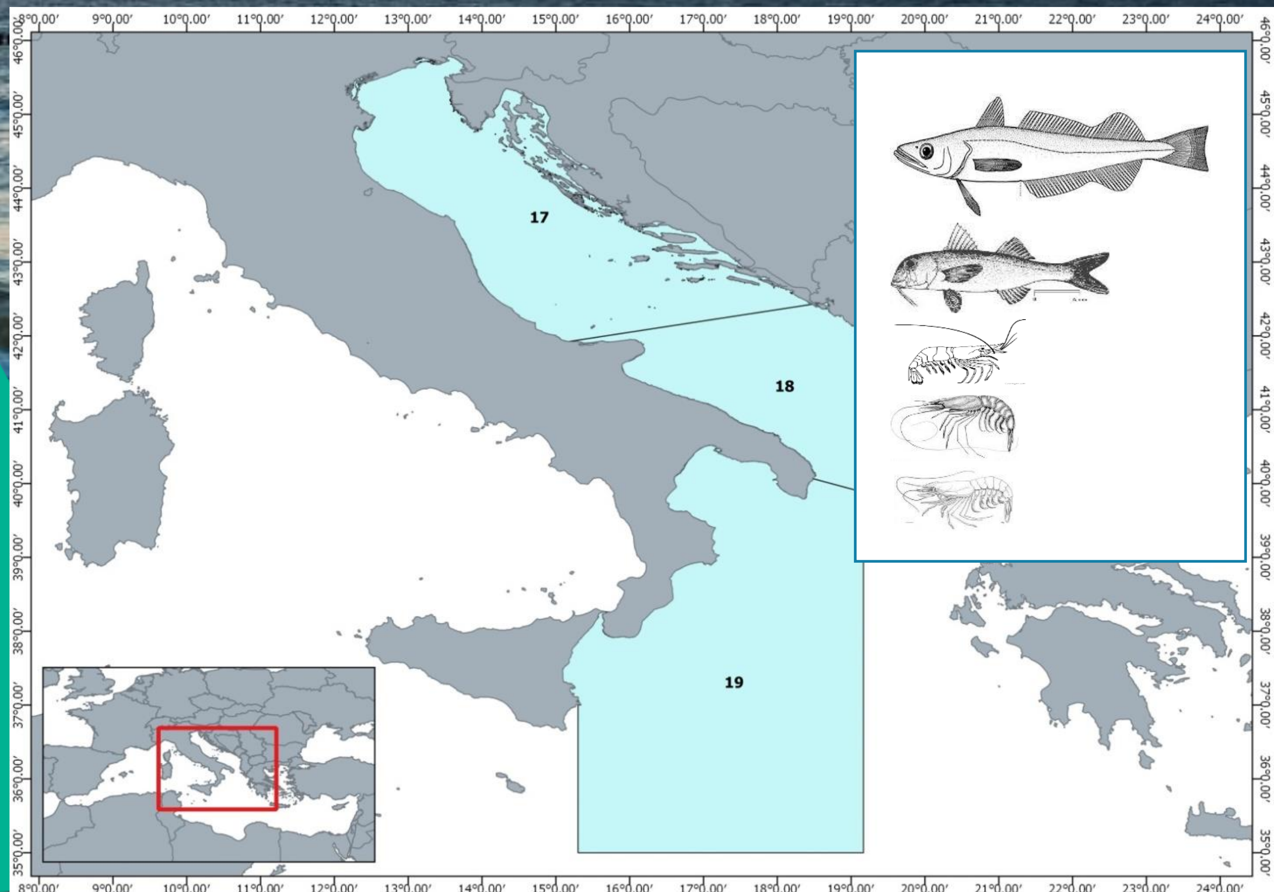
Study area and stocks

- In Mediterranean Sea, where the time series of spawning stocks and recruitments are generally short and poorly contrasted, the fitting of reliable stock-recruitment relationships is still challenging.
- Though, there is evidence that there is a link between environmental factors and the recruitment of key species such as red mullet and European hake (e.g. Levi et al. 2003; Druon et al. 2015).
- Thus, we focused on the estimation of environmentally mediated stock-recruitment relationships (EMSSRs) on demersal stocks in Adriatic and Ionian Sea (GSAs 17-18-19)

Stock	Time span	Working group
European hake GSAs 17-18	1998-2021	GFCM 2022
European hake GSA 19	2004-2022	STECF 2023
Red mullet GSAs 17-18	1972-2022	GFCM 2023
Red mullet GSAs 19	2002-2022	STECF 2023
Deep-water rose shrimp GSAs17-18-19-20	1996-2022	GFCM 2023
Giant red shrimp GSAs 18-19-20	2003-2022	STECF 2023
Blue and red shrimp GSAs 18-19-20	2008-2022	STECF 2023

- **nonlinear (weighted) least square techniques**
- **initial guesses: coefficients estimated by Eqsim (Simmonds et al. 2022)**
- **nls function in R (version 4.2.2)**

process error method applied



Methods

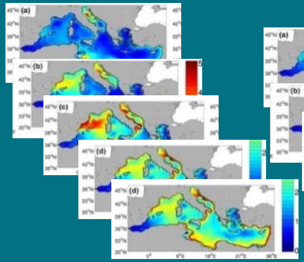
- SSB
- Recruitment

WGSAD 2023

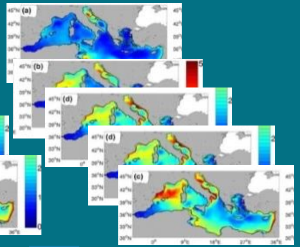
STECF EWG 23-12

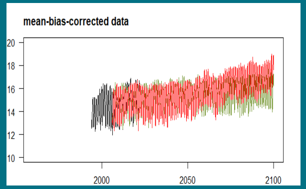
Environmental variables under RCP4.5 and under RCP8.5
annual averages of projected environmental variables on species distribution depth range

RCP4.5

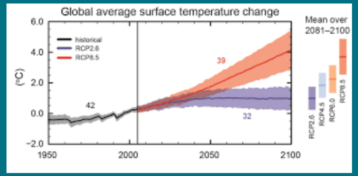


RCP8.5





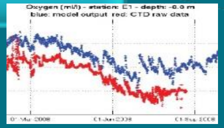
Bias-corrected (Khuen, 2023) monthly projections of environmental data from 3D POLCOMS-ERSEM dataset

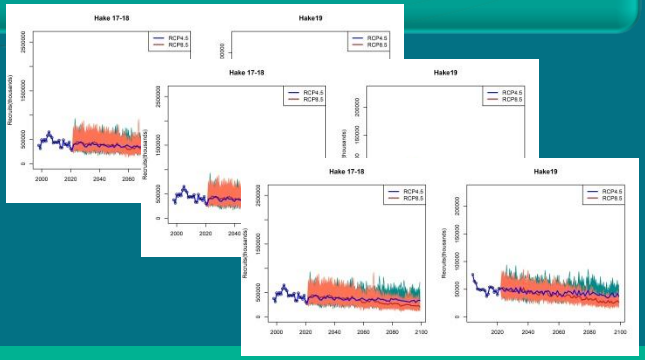


Beverton-Holt, Ricker, hockey stick with no additional covariates

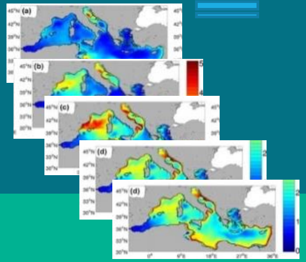
Environmentally mediated stock-recruitment relationship (EMSRR)

Recruitment projections under different climate change scenarios





3D monthly Copernicus Mediterranean reanalysis products



SST, Bottom temperature, Salinity, Bottom salinity, nppv
annual averages of observed environmental variables on species distribution depth range

hindcast (1971-2021) → *Bias-correction*(2006-2021) → *Future projections*(2022-2099)

Beverton-Holt, Ricker and hockey stick stock-recruitment (SR) relationships were extended to include the influence of the environmental variables through an exponential factor, following Hilborn and Walters (1992).

All models were compared with respect to

(**Marc presentation fore more details**):

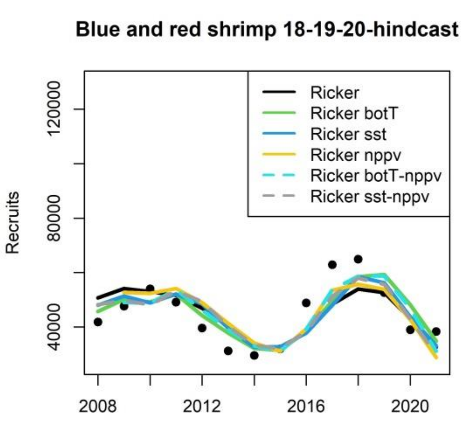
- AIC;
- the Sum of Squared Errors (SSE);
- the Mean Absolute Error (MAE);
- the Root Mean Squared Error (RMSE), given by

$$RMSE = \sqrt{\frac{SSE}{N} + MAE^{2}}.$$

Finally, all models were compared against a model with no additional covariates (only SSB) as naïve solution and scaled accordingly

$$rRMSE = RMSE_{EMSRR}/RMSE_{naive} \text{ and}$$

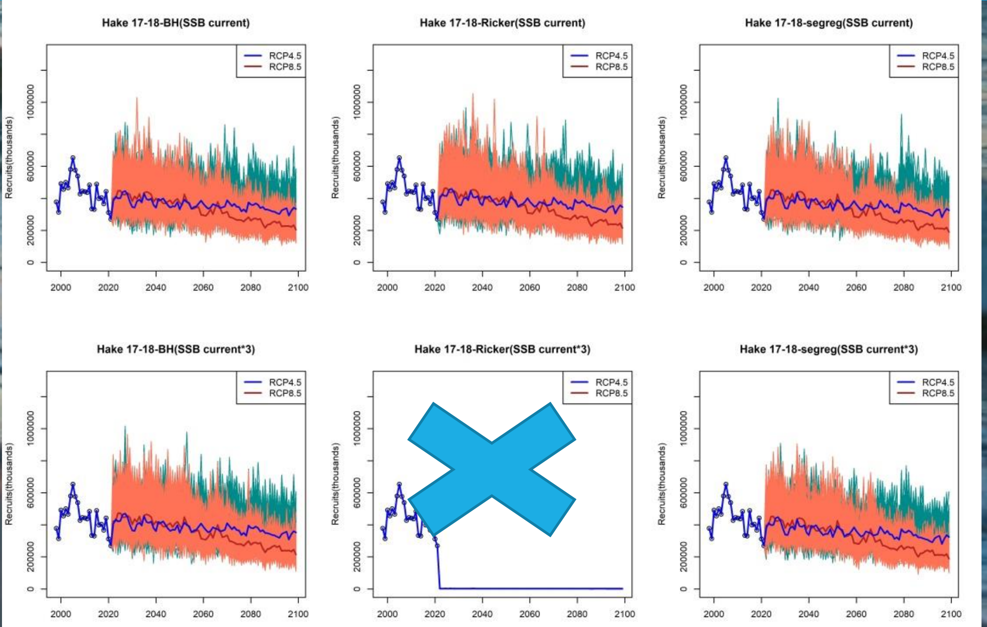
$$rMAE = MAE_{EMSRR}/MAE_{naive}$$



The best model was selected considering the stability of the projection under the two climate scenarios (RCP4.5, RCP8.5) and assuming a constant SSB level equal to:

- **the average of the last 5 years;**
- **three times the average of the last 5 years.**

Model selection predictive capability



Selection of non-correlated environmental variable

Testing SST, botTemp, salinity, botSal, nppv across the depth range where the stocks are distributed (Pearson <0.7)

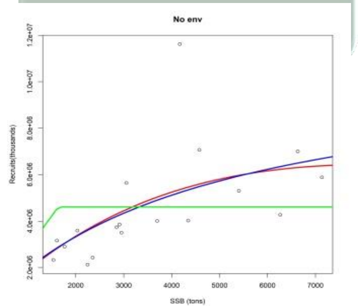
	logS	botT	sst	so	botso	nppv
logS	1.00	0.71	0.45	0.33	0.65	-0.24
botT	0.71	1.00	0.78	0.72	0.93	0.05
sst	0.45	0.78	1.00	0.64	0.66	-0.09
so	0.33	0.72	0.64	1.00	0.70	-0.12
botso	0.65	0.93	0.66	0.70	1.00	0.14
nppv	-0.24	0.05	-0.09	-0.12	0.14	1.00

Fitting classical SRR

BevHolt

Ricker

Hockey stick

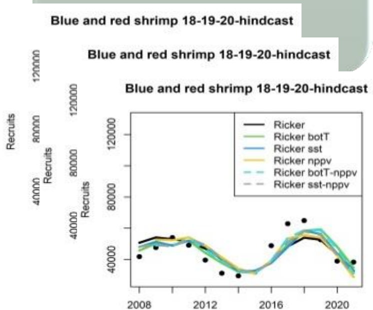


Fitting EMSRR

EM BevHolt

EM Ricker

EM Hockey stick

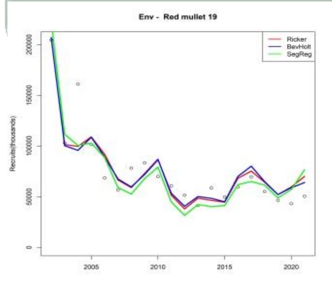


Testing predictive capability

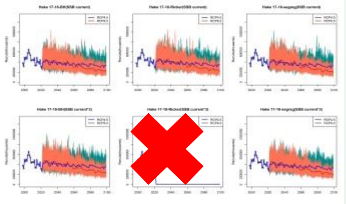
Best EM BevHolt (with smaller rRMSE and rMAE)

Best EM Ricker(with smaller rRMSE and rMAE)

Best EM Hockey stick (with smaller rRMSE and rMAE)



Stability of projections

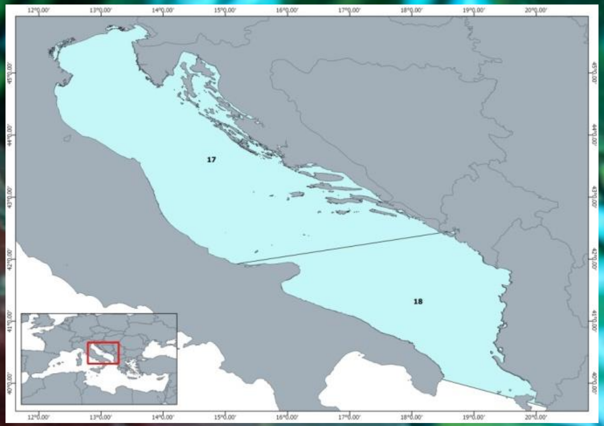


Final model

Practical session

Model selection

European hake GSAs 17-18 – Adriatic Sea



Results

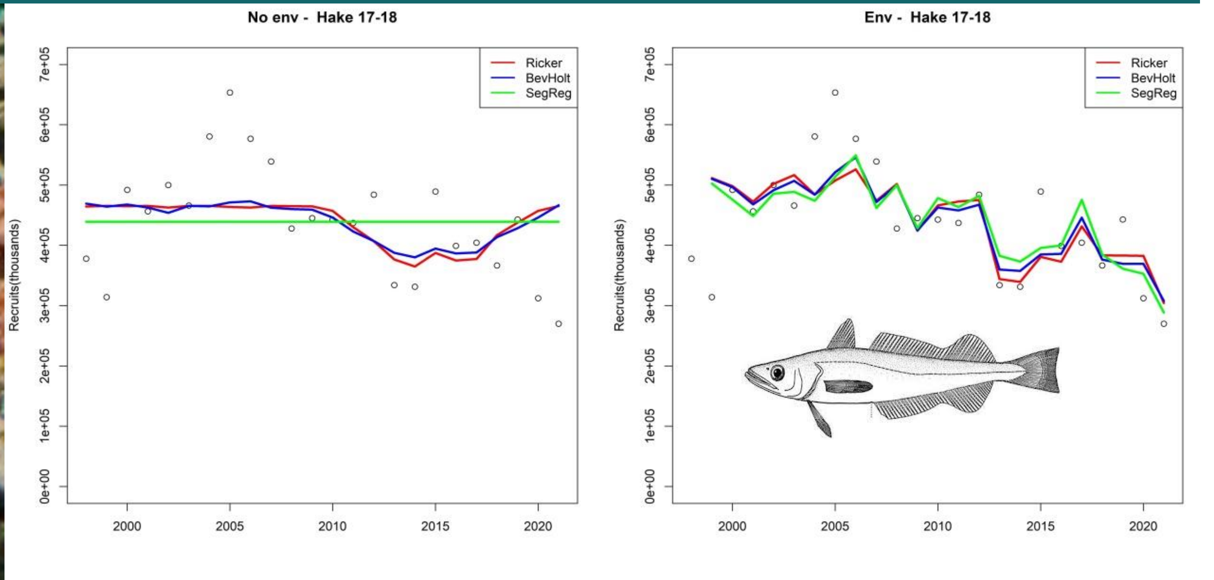
Beverton and Holt

$$R = a * \frac{SSB}{1+b*SSB} * \exp(-c * botT - d * sst),$$

with:
a= 207871, b= 0.00782, c=0. 192 and d=0. 07

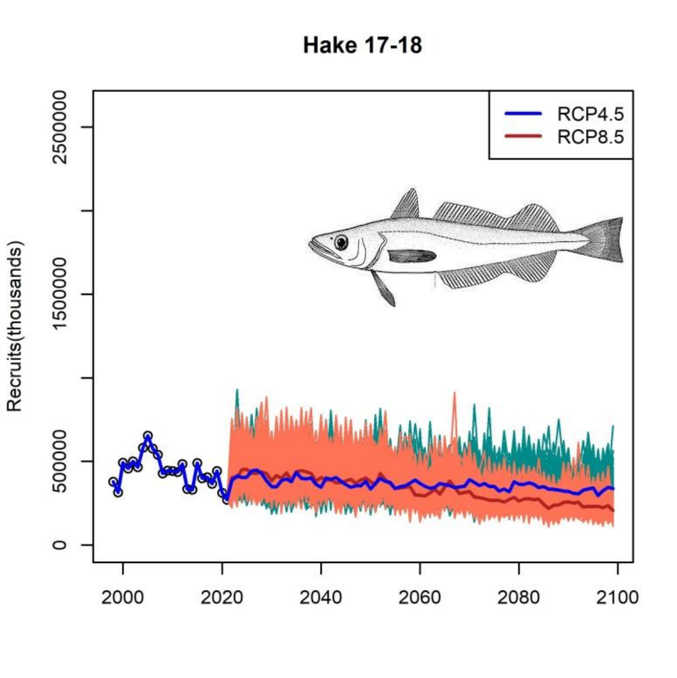
The inclusion of environmental variables in the SRR improved the fitting for all the stocks considered.

In several studies (e.g. Druon et al. , 2015) is highlighted that the thermal preferential bottom temperature for European hake juveniles is between 12 and 15°C (100-200 m of depth).



Assuming the current SSB level until 2099, a **similar level of recruitment is expected** under the two climate scenarios **until 2060**.

After 2060 the model returns **higher values under the RCP4.5** scenario than RCP8.5



BevHolt and hockey stick the models with better rRMSE. **Selected the BevHolt** for consistency with the last assessment.

European hake GSA 19 – western Ionian Sea

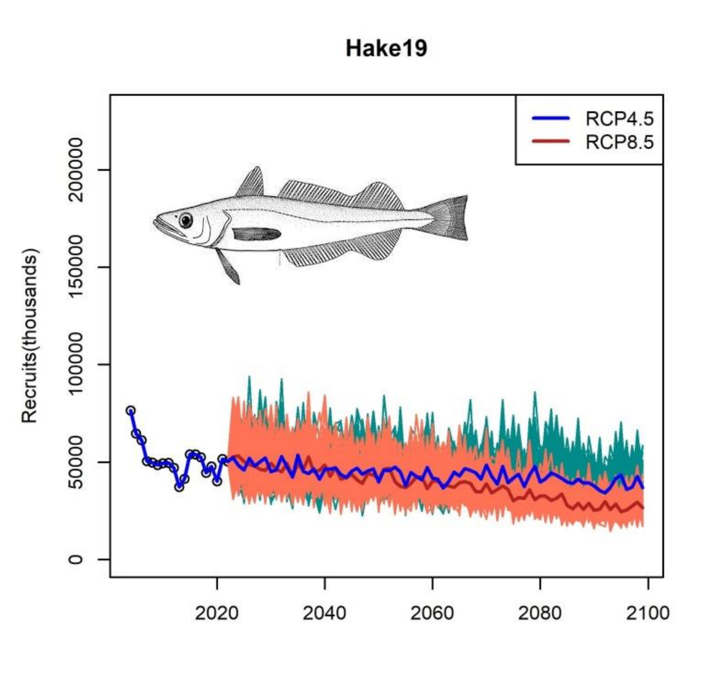
Results

The three explored EMSRR return very similar fittings.

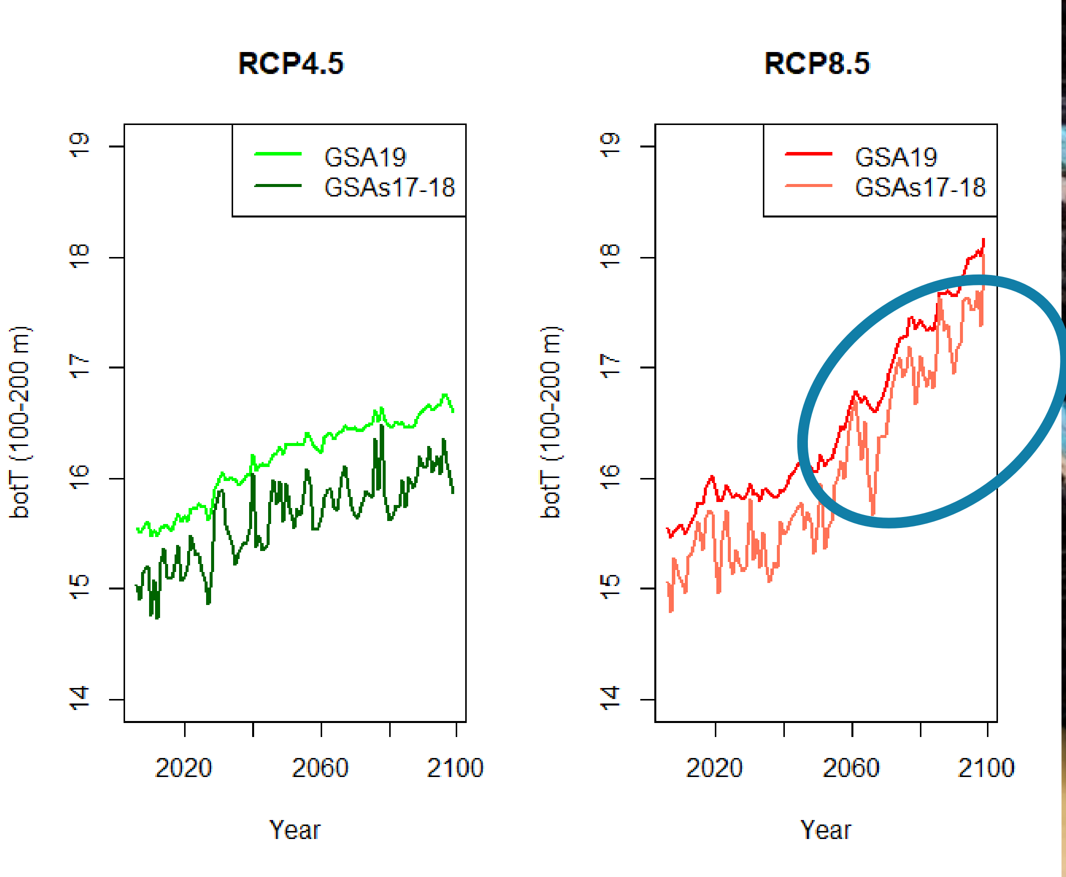
BevHolt selected due to best predictive capability (rRMSE)

$$R = a * \frac{SSB}{1 + b * SSB} * \exp(-c * sst)$$

a=35056, b=0.004, c=0.244



In the western Ionian Sea, the projections under the two climate scenarios are **consistent with the trend estimated for European hake in the Adriatic Sea**.



This could be explained by an **increase in bottom temperature above 16° under RCP8.5 after 2060,** while RCP4.5 remains in all years between 15 and 16° in the bathymetric range of recruits distribution (100-200 m).

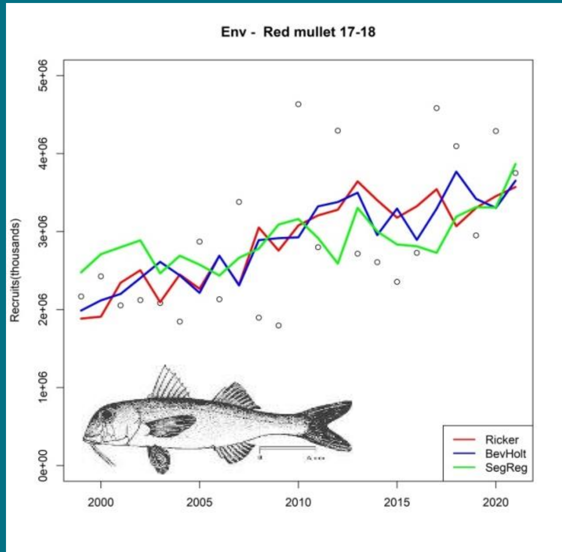
Red mullet in GSAs 17-18 – Adriatic Sea

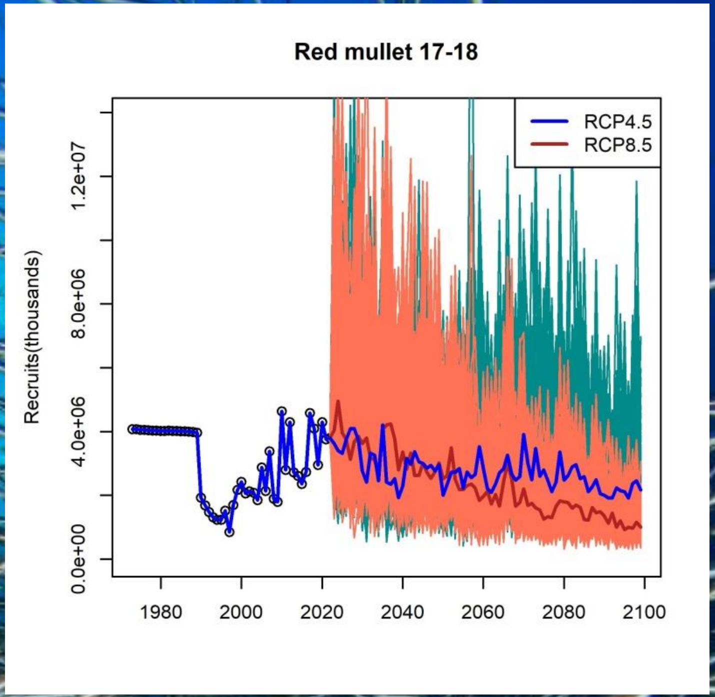
Levi et al. (2003) found that in Strait of Sicily higher red mullet recruitment levels corresponded to warmer SST. The paper fitted different EMSRR and the Ricker was the best performing.

Ricker model including SST and nppv is the best perfoming model, with the rRMSE = 0.61, thus indicating a marked improvement respect to the Ricker S-R without environmental covariates.

$$R = a * SSB * \exp(-b * SSB - c * sst - d * nppv),$$

a=708281.5, b=3.68E-05, c=0.395, d=0.014





Results

For red mullet in Adriatic Sea the recruitment projections show a highly oscillating pattern, similarly with the hindcasting phase.

Also for this stock the overall trend is decreasing under both climate scenarios, quite slowly for RCP4.5 and more sharply for RCP8.5.

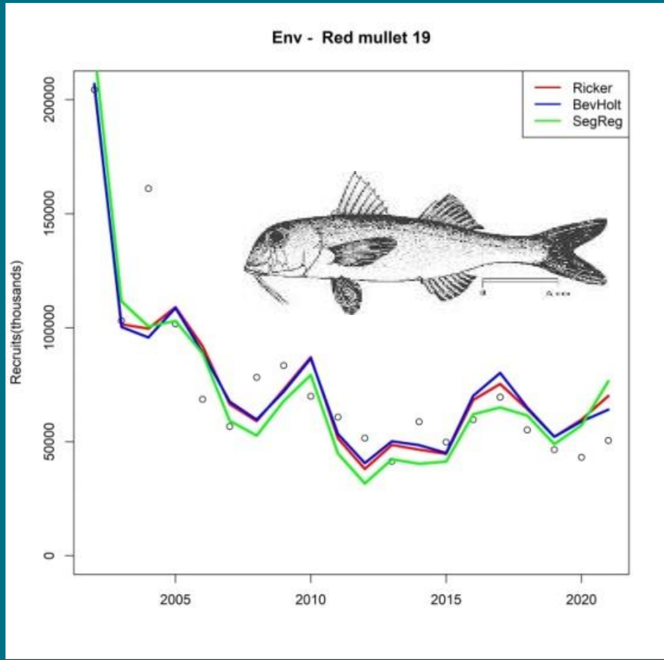
Red mullet in GSA 19 – western Ionian Sea

The model representing the best trade-off is the Ricker, driven by sea surface temperature.

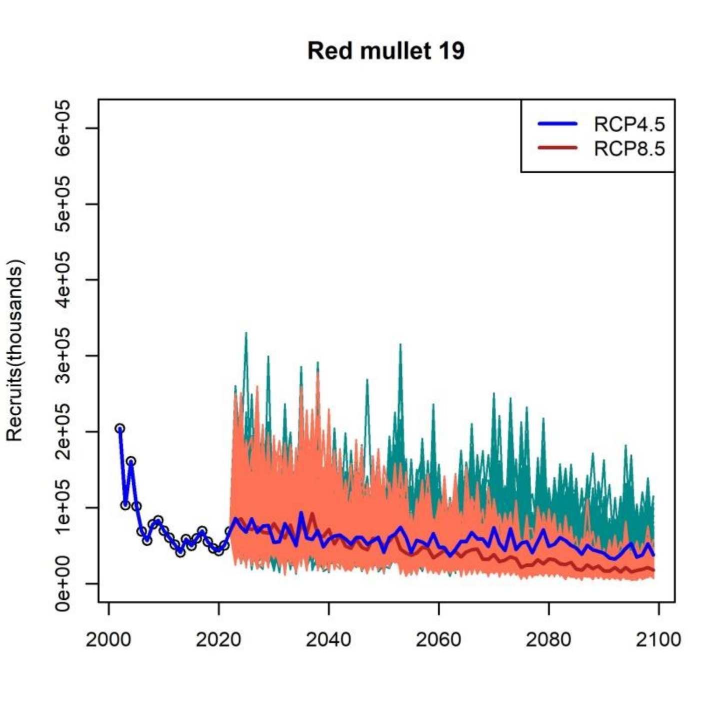
$$R = a * SSB * \exp(-b * SSB - c * sst)$$

a=6209747, b=0.00027, c=0.395, d=0.546

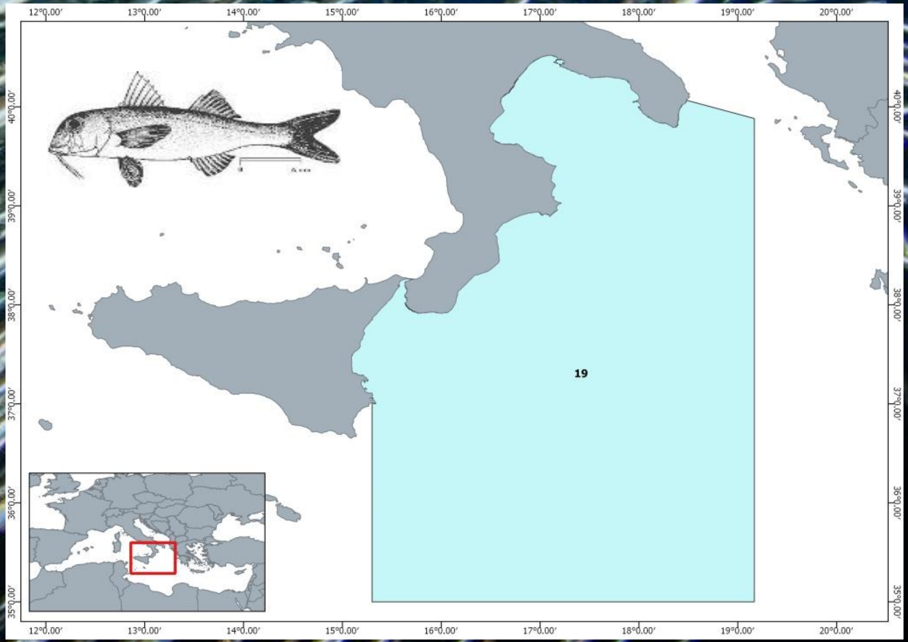
Very similar performances were obtained by Ricker model including SST and nppv, but **the more parsimonious was retained**.



For red mullet in western Ionian Sea the **projections** show a quite **similar level to the historical one** for RCP4.5, while the **RCP 8.5 impact more negatively on the recruitment estimates since 2060 onwards**.



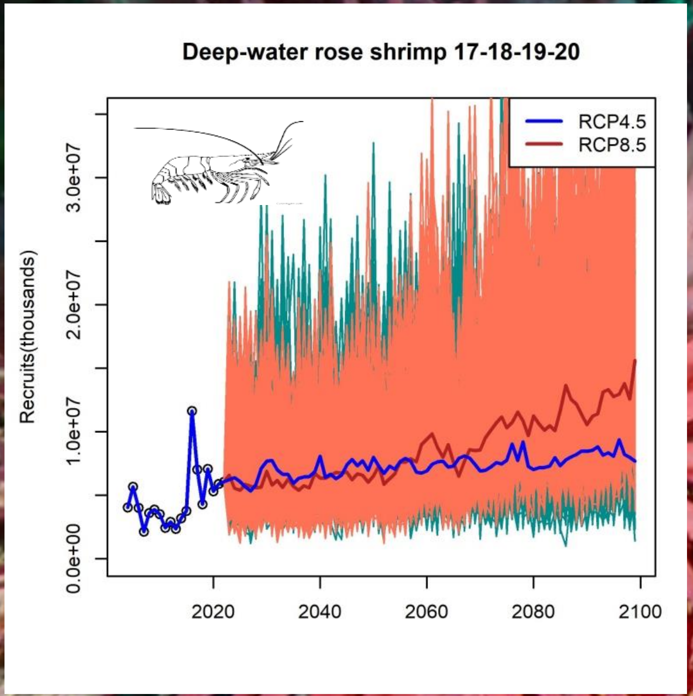
Results



Deep-water rose shrimp GSAs 17-18-19-20 Adriatic and Ionian Seas

Recruitment projections of deep-water rose shrimp show a similar trend between the RCPs until 2060. In the long term, the projections under the RCP8.5 return higher value than RCP4.5, above the historical levels.

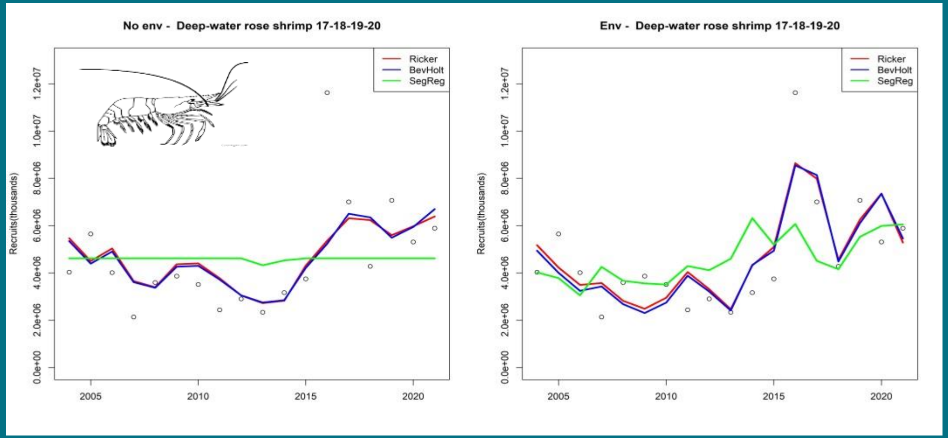
Results



With respect to accuracy and predictive capability (e.g. rMAE and rRMSE) and model stability in projections, the selected environmentally mediated model is the Beverton-Holt, driven by bottom temperature

$$R = a * \frac{SSB}{1+b*SSB} * \exp(-c * botT),$$

a=18.57, b=0.000338, c=-0.35



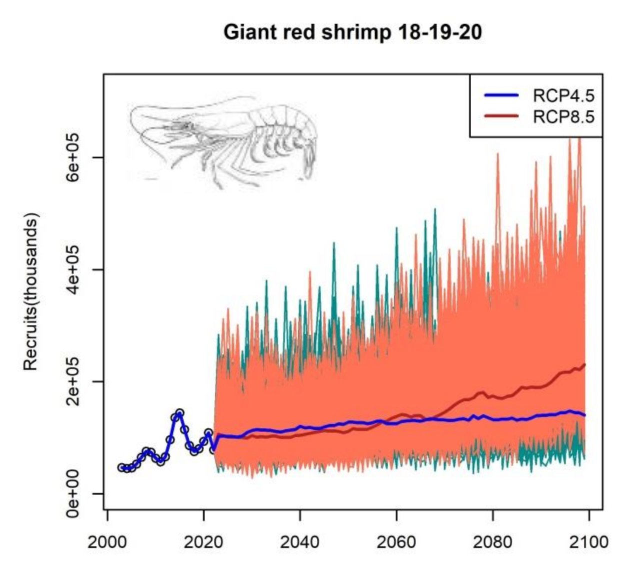
Incorporating the environmental covariates improves the model performance in terms of predictive capability (rRMSE=0.94), while does not in terms of accuracy (rMAE=1.02)

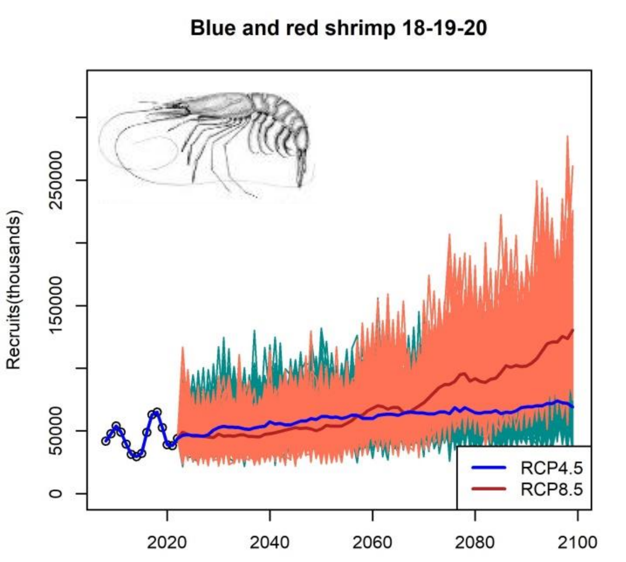
Giant red shrimp and blue and red shrimp GSAs 18-19-20 – Southern Adriatic and Ionian Seas

With respect to accuracy and predictive capability (e.g. rMAE and rRMSE) and model stability in projections, the selected environmentally mediated model in both cases is the Beverton-Holt, driven by bottom temperature

$$R = a * \frac{SSB}{1+b*SSB} * \exp(-c * botT),$$

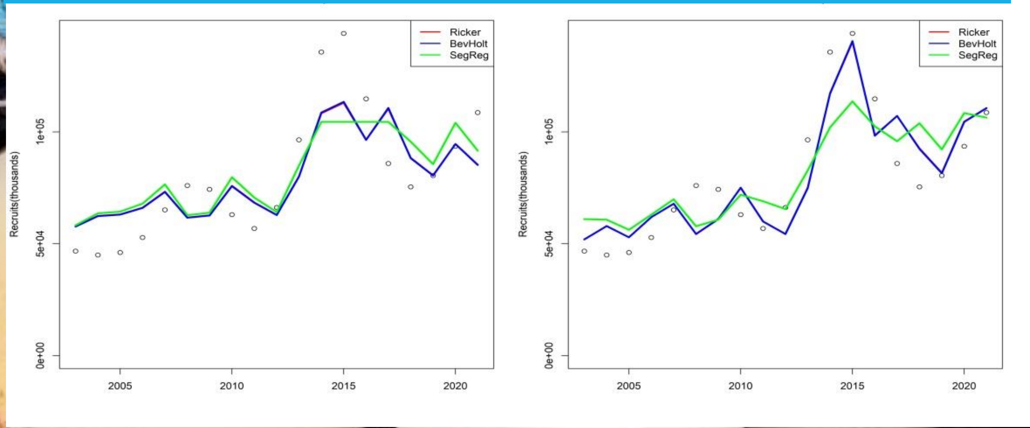
Giant red shrimp: a=1.554, b=0.000129, c=-0.35

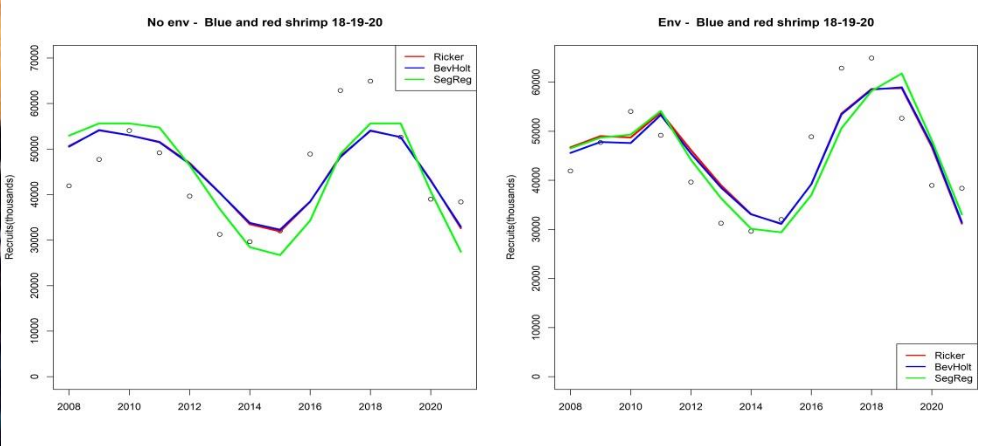




RESULTS

The inclusion of environmental covariates slightly improves the fitting of the model, especially for giant red shrimp.





Also for these shrimps the level of recruitment is quite similar to the historical levels until 2060, while from 2060 the projections show an increase.

Lessons learnt…

This work carried out in Central Mediterranean Sea under SEAwise project represents the first time that environmentally mediated stock-recruitment relationship are estimated in the study area.

- The estimation of the environmentally mediated stock-recruitment relationship using the mechanistic approach is mainly influenced by the **length of the time series and data contrast**.
- The selection of the approach for recruitment fitting (process error versus model error) should be, thus, made according to both aspects.
- Try to **avoid redundancy** in your covariates, selecting non-correlated environmental variables.

Lessons learned…

- Select the best model using the performance metrics, verifying that the prediction capability of the stock-recruitment model shows an **improvement respect to the same model without environmental variables**.
- Compare your results with literature, while **considering the biology of the species** and the specific features of its habitat in the study region.
- The **methodology** here presented can be **easily adapted to the model error approach**, when the data availability allows to estimate SRR coefficients depending on environmental variables.

CONCLUSIONS

Thanks for listening

bitetto@fondazionecoispa.org

Questions?